Ship Steering Autopilot Based on ANFIS Framework and Conditional Tuning Scheme

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Abstract

The ever changing sea condition makes it difficult to use a single mathematical model to describe the nonlinear dynamic behavior of a vessel. Hence, the performance of model-based autopilots is generally inferior to that of model-free designs such as fuzzy controllers or neural networks. This study combines the robustness property of fuzzy logic controllers and the learning capability of artificial neural networks to create an ANFIS (Adaptive Network-based Fuzzy Inference System) ship steering autopilot. In addition, a conditional tuning scheme is presented to increase the response speed of the proposed autopilot, while simultaneously reducing the overshoot. The performance of the proposed autopilot is evaluated by performing a series of course-changing and track-keeping simulations. The simulation results show that the proposed autopilot provides a more adaptive and robust control performance than a traditional PD fuzzy controller under typical sea conditions.

Keywords

Fuzzy Control; Adaptive Network-based Fuzzy Inference System; Autopilot; Track-keeping

Introduction

The automatic steering of ships dates back as far as the invention of the gyrocompass. One of the earliest gyro pilots was presented by Minorsky in the early 1920s, in which a gyrocompass was used to provide heading measurements in order to enable the course correction of automatically steered bodies (Minorsky, 1922; Skjetne, 2003). Broadly speaking, modern autopilot control systems can be categorized as “model-based”, “model-free” or “hybrid”, depending on their mode of operation. Amongst the model-based schemes, the linear-quadratic-Gaussian (LQG) autopilot presented by Holzhüter (1997), the adaptive control scheme demonstrated by Åström and Wittenmark (1989), the Internal Model Control (IMC) approach proposed by Tzeng (1999), and the H_∞ control system developed by Morawski and Pomirski (1998) are the most well known examples. Meanwhile, typical examples of model-free autopilot systems include the fuzzy control scheme proposed by Vaneck (1997), the genetic algorithm-based ship steering control system developed by McGookin et al. (2000), the artificial neural network (ANN) berthing system presented by Zhang et al. (1997), the sliding-mode tracking control of surface model vessel propused by Ashrafiuon et al. (2008) and the SISO and SIMO neural control schemes proposed by Hearn et al. (1997). Finally, typical examples of hybrid-type autopilots include the IMC-ANN system presented by Tzeng and Lu (2003), the fuzzy-sliding mode control scheme proposed by Chen and Hsu (2003), the ANFIS (Adaptive Network-based Fuzzy Inference System) scheme developed by Sutton et al. (1997) and a vessel collision avoidance system using ANFIS method presented by Ahn et al.(2012).

In practice, it is virtually impossible to describe the nonlinear dynamic motion of a vessel in wavy conditions using a single mathematical model. Hence, the performance of traditional model-based autopilots is inevitably constrained by the effects of model uncertainty. However, fuzzy controllers and ANN control schemes do not require an explicit modeling of the plant and therefore providing a better robustness and adaptive performance than model-based methods.

In fuzzy control systems, the output response is determined by a set of fuzzy rules and membership functions. In practice, the design of the membership function has a significant effect on the output response of the fuzzy controller. Thus, in implementing fuzzy-based control schemes, it is essential that the membership functions are properly defined. Accordingly, the authors in (Jang, 1993) presented an ANFIS (Adaptive Network-based Neuro-Fuzzy Inference System) framework, in which the fuzzy logic controller was integrated with an ANN in order to learn the most appropriate membership function parameters.

In the present study, the ANFIS framework proposed in (Jang, 1993) is applied to realize a fuzzy-based ship steering autopilot. The performance of the proposed autopilot is enhanced by means of a conditional tuning scheme, designed to increase the response speed, while simultaneously reducing the amount of overshoot via an appropriate tuning of the input and output gains of the fuzzy controller. The effectiveness of the proposed autopilot is evaluated by performing a series of course-changing and track-keeping simulations in a Matlab/Simulink environment. It is evident that the proposed ANFIS framework provides a more adaptive and robust ship steering capability than a traditional PD fuzzy controller.

Track-keeping Guidance Method

Figure 1 illustrates the basic structure of the ship steering autopilot developed in the present study. As shown, the track-keeping mission is accomplished through a series of course-changing maneuvers, in which the conventional line-of-sight (LOS) guidance scheme is used to calculate the required reference heading in each case.

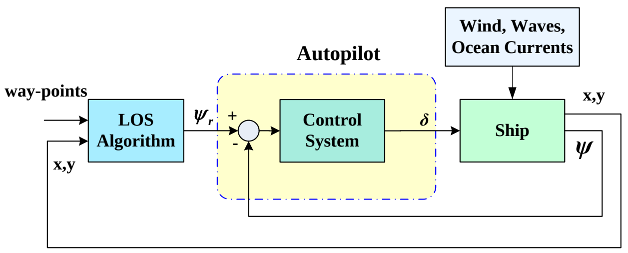

FIG. 1 CONFIGURATION OF PROPOSED TRACK-KEEPING AUTOPILOT SYSTEM

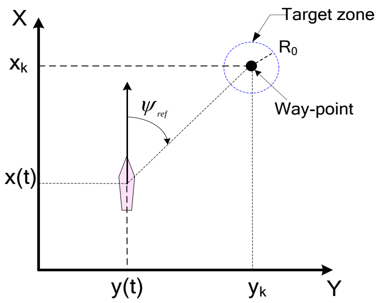

FIG. 2 LOS GUIDANCE CONCEPT

Figure 2 presents a schematic illustration of the LOS concept. Basically, the LOS is an imaginary line stretching between the vessel and the target (a way-point marker in the present case). To reach this way-point, the vessel must adjust its heading via a reference heading angle ψ_{ref}, given by

$$\psi_{ref}(t) = \tan^{-1}\left(\frac{y_k - y(t)}{x_k - x(t)}\right) \tag{1}$$

where (x_k, y_k) are the coordinates of the way-point and $(x(t), y(t))$ are the positional coordinates of the vessel.

In performing the track-keeping mission, the aim is to steer the vessel in such a way that it enters the target zone at each way-point along the reference path. In accordance with the recommendations of Fossen (2002), the radius of the target zone, R_0, is specified as approximately two ship lengths. Once the vessel has entered the target zone, i.e.,

$$(x_k - x(t))^2 + (y_k - y(t))^2 \le R_0^2 \tag{2}$$

the track-keeping autopilot automatically selects the next way-point (x_{k+1}, y_{k+1}) along the reference path and resets the reference heading angle accordingly.

Fuzzy Control Approach for Ship Steering Autopilot

Fuzzy systems have been widely applied in many fields, including signal processing, communications, control and expert systems, and so on. Fuzzy systems can be used as either open-loop controllers or closed-loop controllers. Figure 3 shows a typical closed-loop system.

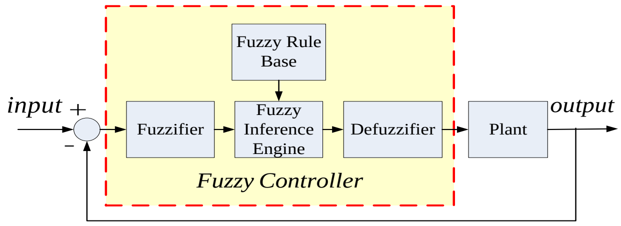

FIG. 3 BASIC CONFIGURATION OF CLOSED-LOOP FUZZY CONTROL SYSTEM

In implementing a fuzzy control system, the real-valued input is fuzzified by a fuzzifier and processed by the fuzzy inference engine in accordance with a set of fuzzy rules. The output of the fuzzy interference engine is then defuzzified and supplied as a control signal to the plant. As discussed in Section 1 (Introduction), the performance of a fuzzy system is dependent not only on the fuzzy IF-THEN rules, but also on the design of the membership functions, e.g., Triangular, Gaussian (Pi), S-function, and so on (Wang, 2005). Having processed the fuzzified input, the output of the fuzzy inference engine is defuzzified using one of several different methods, including Max Grade, Maximum, Center of Area, Center of Average, or Height and Center of Sums (Wang, 2005). Through these processes, there is an important advantage that the fuzzy systems theory is provided a systematic procedure for transformation of the knowledge base into a nonlinear mapping.

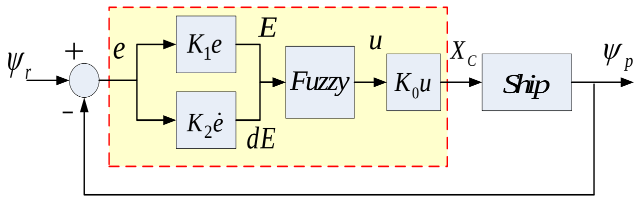

FIG.4 PD-TYPE FUZZY CONTROLLER STRUCTURE

The autopilot system developed in the present study is based on the PD-type fuzzy controller structure shown in Fig. 4. Note that ψ_r is the reference heading angle calculated using the LOS guidance scheme, e is the heading error signal, E and dE are the input heading error and yaw error, respectively, u is the defuzzified control signal, Xc is the output command, and ψ_p is the system output. As shown, the controller has two input gains ($K_1 e$ and $K_2 \dot{e}$) and one output gain ($K_0 u$). The input gains map the inputs of the fuzzy system to the input universe of discourse, while the output gain scales the output of the controller to the output universe of discourse. It is noted that for all three gains, the universes of discourse are normalized in the range of [-1, 1]. For the ship steering controller developed in the present study, the universe of discourse for the input heading error is specified as [-60˚, 60˚], while that for the input yaw error is set as [-4˚/s, 4˚/s] and that for the output rudder command is chosen as [-35˚, 35˚]. In addition, the widths of the universes of discourse for the input heading error and yaw error are both set as [-6, 6], while that of the universe of discourse of the output rudder command is set as [-7, 7]. As a result, the default settings for the two input (normalizing) gains are $K_1 = 6/60 = 0.1$ and $K_2 = 6/4 = 1.5$, respectively, while that for the output gain (scale factor) is $K_0 = 35/7 = 5$. Finally, the fuzzy controller is implemented using the Max-Min Composition fuzzy inference method and the Center of Gravity defuzzifier (Wang, 2005).

Figures 5 ~ 7 illustrate typical membership functions for the heading error, yaw error, and rudder command, respectively. Meanwhile, Table 1 shows the fuzzy rules used by the fuzzy controller in determining the rudder commands required to accomplish the course-changing and track-keeping maneuver.

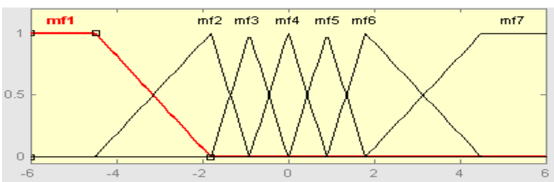

FIG.5 MEMBERSHIP FUNCTIONS OF HEADING ERROR *E*

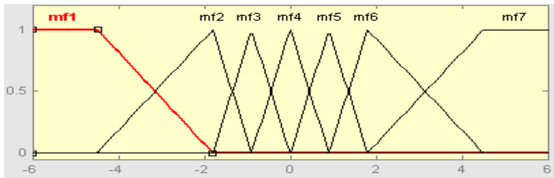

FIG.6 MEMBERSHIP FUNCTIONS OF YAW ERROR *dE*

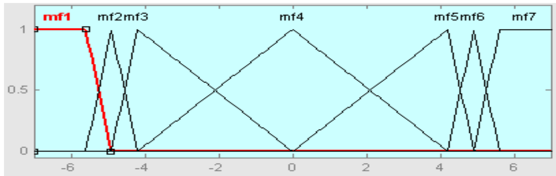

FIG.7 MEMBERSHIP FUNCTIONS OF RUDDER COMMAND

TABLE 1. FUZZY CONTROL RULES

E \ dE	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

ANFIS Approach for Ship Steering Autopilot

The ANFIS method is the main research of Jang's PhD thesis (Jang, 1992). These techniques provide a tool to learn information from prepared data bank for the fuzzy modelling process. The optimization and adaptation of many parameters in fuzzy inference system rules can be implemented through the learning process of artificial neural network. In this section, the performance of the fuzzy-based ship steering autopilot described in Section III is enhanced by means of an ANFIS (Adaptive Network-based Fuzzy Inference System) framework, in which the membership functions of the fuzzy inference engine are optimized by an artificial neural network (ANN). In this study, ANFIS uses a hybrid learning algorithm to identify the membership function parameters of two inputs with single-output, the fuzzy consequences of first-order Sugeno type rules of the form:

$$\text{If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ then } \delta_1 = p_1 x_1 + q_1 x_2 + r_1 \quad (3)$$

where x_1 and x_2 are the input vector, δ_1 is the output vector and $\{p_1, q_1, r_1\}$ are the consequent parameters of this rule. The membership function parameters will be tuned by using the ANFIS method.

Figure 8 illustrates the first order Sugeno fuzzy model with corresponding ANFIS layer architecture. A total five layers structure was adopted in the ANFIS design process. Note that $O_{1,ij}$ denotes the output of the i-th

node with j-th member set in the first layer.

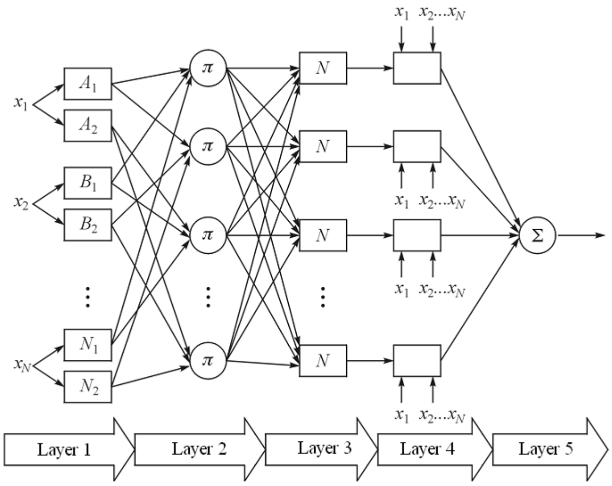

FIG.8 LAYER STRUCTURE OF ANFIS

Layer 1 Each node in this layer will generate a membership grade of a linguistic label. For example, the node function of the i-th node may be a generalized bell membership function as follow:

$$O_{1,\ ji} = \mu_j(x_i) = \frac{1}{1+\left|\frac{x_i - c_{ji}}{a_{ji}}\right|^{2b_{ji}}} \quad (4)$$

$$for\ i = 1, 2, ..., N;\ j = 1, 2, ..., M_i$$

where x_i is the input to node I; $\mu_j(x_i)$ is the linguistic label (*small*, *large*, *etc*.) associated with this node; {a_{ji}, b_{ji}, c_{ji}} is the parameter set. Parameters in this layer are referred to as premise parameters.

Layer 2 Each node in this layer labelled Π which multiplies the income signals and sends the product out. For example,

$$O_{2,\ p} = w_p = \prod_{i=1}^{N} \mu_{j_i}(x_i) \quad (5)$$

$$\text{for } j_i = 1,\ ...,M_i;\ \ p = 1,\ ...,\ P$$

where w_p represents the firing strength; *T-norm* operators that perform generalized AND can be used as the node function in this layer.

Layer 3 Each node of this layer computes the proportion of the rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,p} = \overline{w}_p = \frac{w_p}{\sum_{p=1}^{P} w_p} \quad (6)$$

Layer 4 Each node in this layer has the following function:

$$O_{4,p} = \overline{w}_p f_p = \overline{w}_p \left(\sum_{1}^{p} p_p x_1 + q_p x_2 + r_p \right) \quad (7)$$

where $\overline{w}_p$ is the output of layer 3, {p_p, q_p, r_p} is the parameter set. Parameters in this layer are referred to as the consequent parameters.

Layer 5 The single node in this layer calculates the overall outputs as the summation of all incoming signals:

$$O_{5,1} = \sum_{p=1}^{P} \overline{w}_p f_p = \frac{\sum_{p=1}^{P} w_p f_p}{\sum_{p=1}^{P} w_p} \quad (8)$$

The constructed adaptive network in Fig. 8 is functionally equivalent to a fuzzy inference system.

Figure 9 illustrates the basic configuration of the ANFIS autopilot. As shown in Fig. 10, the ANN comprises two inputs (corresponding to the heading error and yaw error, respectively) and one output (corresponding to the rudder command). The ANFIS parameters optimization method options available for Fuzzy Inference System training are hybrid and backpropagation. Error tolerance is used to create a training stopping criterion, which is related to the error size.

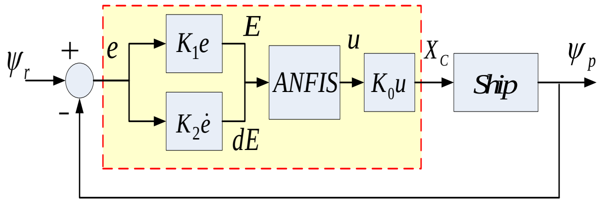

FIG. 9 BASIC CONFIGURATION OF ANFIS SHIP STEERING AUTOPILOT

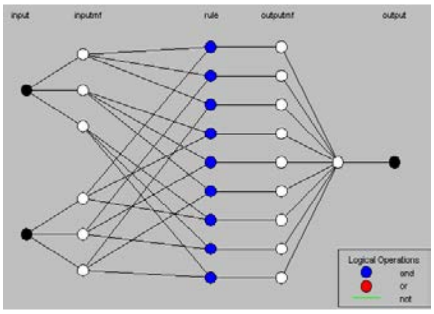

FIG. 10 ANN USED TO TRAIN MEMBERSHIP FUNCTIONS OF ANFIS SHIP STEERING AUTOPILOT

Three membership functions are assigned to each input, and thus a total of nine fuzzy rules are required (as indicated by the blue circles in Fig. 10). Note that for both the input nodes and the output node, the membership functions have the form of a generalized bell shape.

In optimizing the parameters of the membership functions using the ANFIS framework, it is desirable to use heading and rudder command data obtained from real-world track-keeping maneuvers. However, for reasons of cost and practicality, the input and

output data used in the present study were obtained from numerical simulations performed using the fuzzy ship steering autopilot described in previously Section.

The optimal values of the membership function parameters were determined via a training process performed using a back-propagation (BP) algorithm based on the gradient steepest descent method. During the training process, the error was quantified using a least-squares metric. Note that the error was defined as the difference between the training data (output rudder command) and the ANFIS output command. The training process terminated once the error reduced to a value less than 0.01. The training procedure was performed using 75% of the data generated in the fuzzy controller simulations. Having trained the ANFIS framework, it was tested using the remaining 25% of the simulation data.

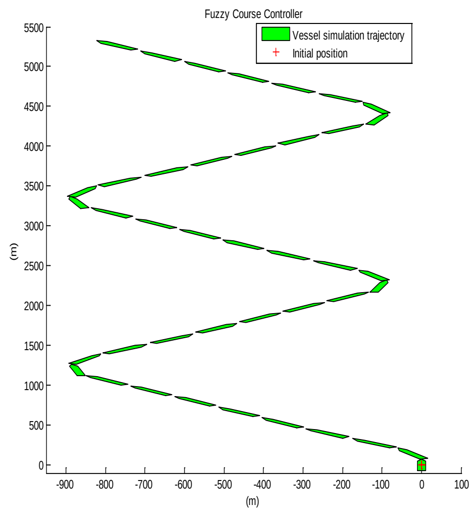

FIG. 11 SIMULATED VESSEL TRAJECTORY (±40° ZIG-ZAG)

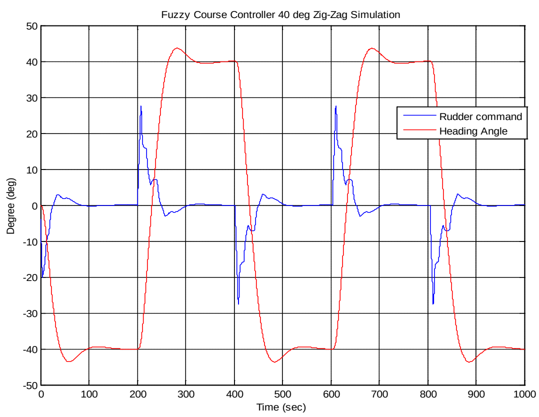

FIG.12 HEADING ANGLE AND RUDDER COMMAND RESPONSE DURING SIMULATED ±40° ZIG-ZAG TRACK-KEEPING TASK

In order to train the ANFIS controller over a wide range of heading changes and rudder commands, the fuzzy controller simulations reproduced the ±40° zig-zag trajectory shown in Fig. 11. The corresponding heading angle and rudder commands issued by the fuzzy autopilot are shown in Fig. 12. The total simulation time was set as 1000 seconds, while the sampling rate was set as 0.1 seconds; giving a total of 10000 pairs of I/O data for training and testing purposes. It is to be noted that the training data was without wave disturbance. The main purpose is to show the ANFIS system robustness of disturbance rejection.

Figures 13 and 14 show the untrained membership functions of the heading angle error and yaw error, respectively. Figures 15 and 16 show the equivalent membership functions following the training process. Finally, Fig. 17 shows the overall input-output contour plot of the ANFIS controller. In another way, the Fig.17 represents the control surface, the widely used the center of area method strategy generates the center of gravity of the possibility distribution of a control action.

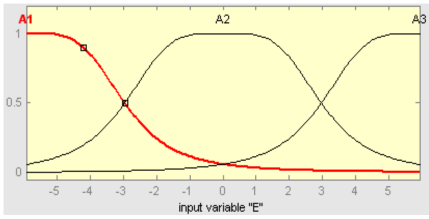

FIG.13 UNTRAINED MEMBERSHIP FUNCTION OF *E*

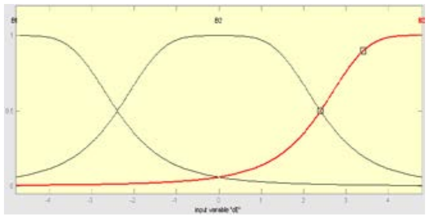

FIG.14 UNTRAINED MEMBERSHIP FUNCTION OF *dE*

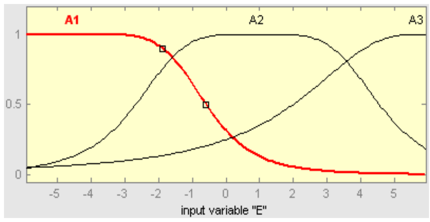

FIG.15 ANFIS TRAINED MEMBERSHIP FUNCTION OF *E*

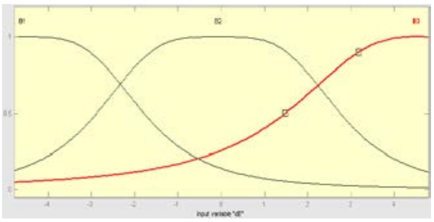

FIG.16 ANFIS TRAINED MEMBERSHIP FUNCTION OF *dE*

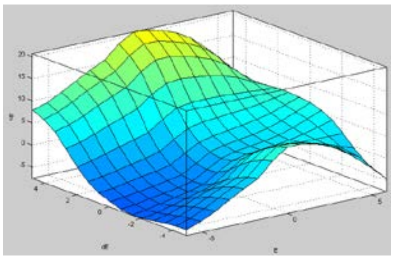

FIG.17 I/O CONTOUR PLOT OF ANFIS CONTROLLER

Simulation Trials and Results

The steering capabilities of the fuzzy-based autopilot (Section 3) and trained ANFIS autopilot (Section 4) were evaluated by performing a series of simulated course-changing and track-keeping tasks using a Nomoto ship model with a length of 150 m and breadth of 22 m. In accordance with the ship model, the rudder gain was specified as k=0.32 (sec^{-1}) and the time constant was set as T= 34.2 (sec). In performing the simulations, it was assumed that the vessel was perturbed by the following wave disturbance, generated by passing a white noise throught a second order shaping filter given by Fossen (2002) as follows:

$$d_o = (\frac{K_w s}{s^2 + 2\xi w_e s + w_e}) * w(s) \tag{9}$$

in which d_o represents the output disturbance, ξ is the damping coefficient; w_e is the wave encounter frequency; and K_w is a wave intensity constant, and depends on the dominant wave frequency, the forward speed of the ship, and the angle between the heading of the ship and the direction of the waves.

This approach has an advantage as its simplicity for simulation purposes. In the current simulations, ξ, w_e and K_w were assigned values of 0.05, 0.6 and 2.5, respectively, which resulted in a narrow band type of disturbance to the vessel and induced about ±8° heading error of disturbance. It gave a good qualited description of irregular waves. However, additional research is required to find a general expression between the sea-state parameters, the vessel dynamics and the disturbance model parameters.

Course-Changing Task Without Wave Disturbance

Figure 18 shows the simulation results obtained for the heading angle and rudder response of the fuzzy and ANFIS autopilots when performing a simple 60˚ course-changing maneuver in the absence of environmental disturbances. As discussed in Section 3, the universe of discourse for the input heading error of the fuzzy controller was specified as [-60˚, 60˚].

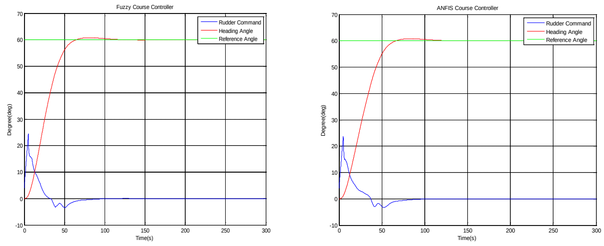

FIG.18 HEADING ANGLE AND RUDDER RESPONSE OF FUZZY AUTOPILOT (LEFT) AND ANFIS AUTOPILOT (RIGHT) WHEN PERFORMING 60˚COURSE-CHANGING TASK IN ABSENCE OF WAVE DISTURBANCE

Moreover, the ANFIS autopilot was trained using the I/O data obtained from the fuzzy autopilot. Thus, as shown in Fig. 18, the heading angles and rudder responses of the two autopilots are very similar.

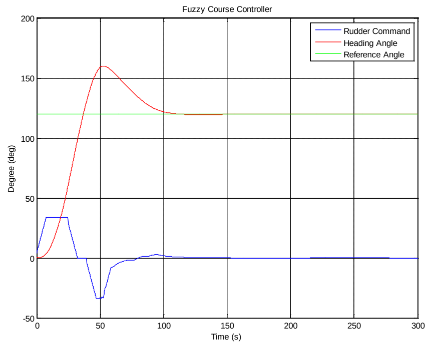

FIG.19 HEADING ANGLE AND RUDDER RESPONSE OF FUZZY AUTOPILOT WHEN PERFORMING 120˚COURSE-CHANGING TASK IN ABSENCE OF WAVE DISTURBANCE

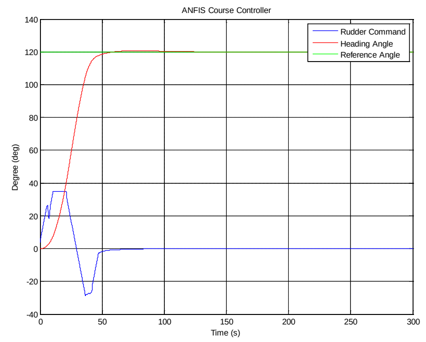

FIG.20 HEADING ANGLE AND RUDDER RESPONSE OF ANFIS AUTOPILOT WHEN PERFORMING 120˚COURSE-CHANGING TASK IN ABSENCE OF WAVE DISTURBANCE

Figures 19 and 20 show the heading angle and rudder response of the fuzzy autopilot and ANFIS autopilot, respectively, when performing a 120˚ course-changing task (Note that the effects of environmental disturbances are once again neglected). It is observed that the heading response of the fuzzy autopilot exhibits a greater overshoot than that of the ANFIS autopilot and takes a longer time to reach steady-state conditions. This result is to be expected since the input heading error (120˚) lies outside of the original

universe of discourse [-60˚, 60˚], and thus the fuzzy controller provides a less precise and slower response. In general, the results presented in Figs. 19 and 20 show that the ANFIS autopilot provides a more robust and efficient performance than the fuzzy control system due to the overshot angle in Fig.20 less than which shown in Fig. 19 and even the steady state performance of ANFIS better than it shown in Fig.19.

Conditional Tuning of ANFIS system

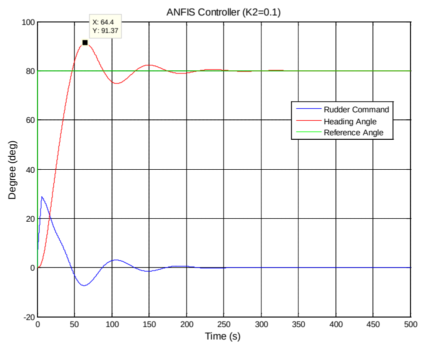

FIG.21 HEADING ANGLE AND RUDDER RESPONSE OF ANFIS AUTOPILOT WHEN PERFORMING 80˚ COURSE-CHANGING TASK GIVEN K_2=0.1

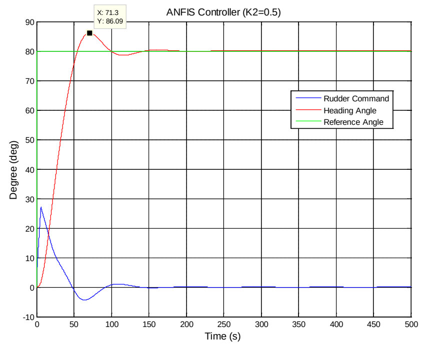

FIG.22 HEADING ANGLE AND RUDDER RESPONSE OF ANFIS AUTOPILOT WHEN PERFORMING 80˚ COURSE-CHANGING TASK GIVEN K_2=0.5

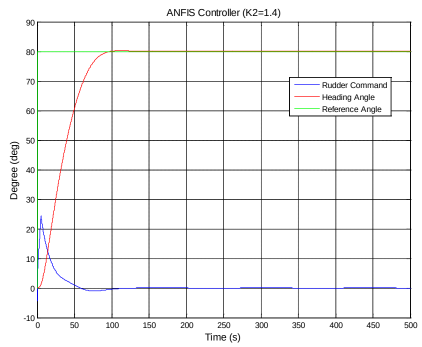

FIG.23 HEADING ANGLE AND RUDDER RESPONSE OF ANFIS AUTOPILOT WHEN PERFORMING 80˚ COURSE-CHANGING TASK GIVEN K_2=1.4

Ideally, any controller should provide a rapid response and no overshoot. The previous section has demonstrated that the ANFIS controller provides a better control performance than the traditional PD-type fuzzy controller. The present section proposes a conditional tuning scheme for further improving the response speed of the ANFIS controller, while simultaneously reducing the overshoot. The normalizing gains K_1, K_2 and the scale factor K_0 have been shown in the Fig.4 (Fuzzy) and Fig.9 (ANFIS) which have the capability to change the input and output universe of discourse ranges. If this advantage can be fully utilized, then the perfect controller may be achievable.

To evaluate the effect of the yaw error gain on the response time and overshoot of the ANFIS controller, the input heading error gain and rudder command gain were assigned constant values of K_1=0.075 and K_0=5, respectively, while the yaw error gain was assigned values of K_2=0.1, 0.5 and 1.4. The corresponding simulation results for an 80˚ course-changing task are presented in Figs. 21 ~ 23, respectively.

Comparing the three figures, it is seen that the system overshoot reduces with an increasing value of K_2, but the response time increases. Accordingly, the performance of the ANFIS autopilot proposed in Section IV has been enhanced by means of the conditional tuning structure shown in Fig. 24; designed to automatically switch the normalizing gains and scale factor by pre-testing the response effect. This is the main idea to design the conditional tuning of ANFIS system in which the better performance can be achieved simultaneously both increasing the response speed and reducing the system overshoot.

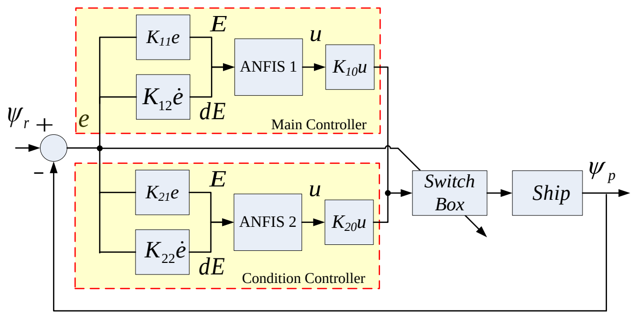

FIG.24 BASIC STRUCTURE OF CONDITIONAL TUNING ANFIS CONTROLLER

As shown in Fig. 24, the conditional tuning ANFIS autopilot has a parallel structure. In other words, only a single output command is issued to the control plant. It is also noted that the switch box is connected to the input error signal. That is, the controller response depends on the magnitude of the error signal. In the

present simulations, an error signal range of ±10˚ was taken as a trigger in activating ANFIS 2 in Fig. 24. Specifically, if the absolute value of the error signal was less than 10˚, the original gains of the ANFIS autopilot (i.e., ANFIS 1) kept unchanged. However, if the absolute value of the error signal was greater than 10˚ (i.e., the system response needs to work harder than before), so the critical condition can be used to speed up the system response and sacrifice some system performance such as overshoot. In other words, the normalized and scaling gains of the ANFIS autopilot were conditioned in such a way as to accelerate the system response at the expense of a slightly higher overshoot.

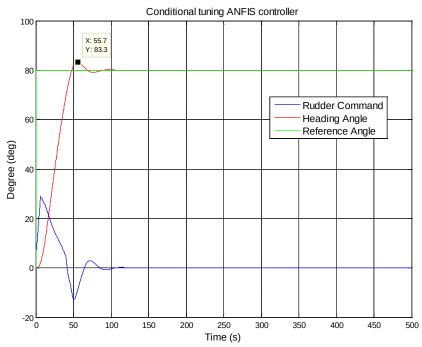

FIG.25 HEADING ANGLE AND RUDDER RESPONSE OF CONDITIONAL TUNING ANFIS CONTROLLER WHEN PERFORMING 80˚ COURSE-CHANGING TASK IN ABSENCE OF WAVE DISTURBANCE

Figure 25 illustrates the simulated response of the conditional tuning ANFIS autopilot when performing an 80˚ course-keeping task in the absence of wave disturbances. It can be seen that the controller achieves both a rapid response time and a reduced overshoot. Based on inspection, the total overshoot angle is just 3.3˚, while the response time is less than 50 seconds. By contrast, under the original ANFIS control scheme, the overshoot angle and response time are 11.3 degree (see Fig.21) and more than 50 sec (see Fig. 23), respectively. Thus, the superior performance of the conditional tuning ANFIS framework is confirmed.

Figure 26 shows the response of the conditional tuning ANFIS controller when performing the 80˚ course-changing task in the presence of wave disturbances. Meanwhile, Fig. 27 shows the response of the conditional tuning ANFIS controller when performing the ±40˚ zig-zag track-keeping task in the presence of wave disturbances. It is evident that the heading responses of both course keeping (in Fig. 26) and zig-zag track-keeping missions (in Fig. 27) were fitted to the task under the wave disturbances.

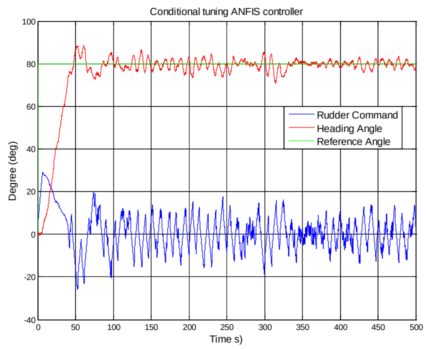

FIG. 26 HEADING ANGLE AND RUDDER RESPONSE OF CONDITIONAL TUNING ANFIS CONTROLLER WHEN PERFORMING 80˚ COURSE-CHANGING TASK IN PRESENCE OF EXTERNAL DISTURBANCES

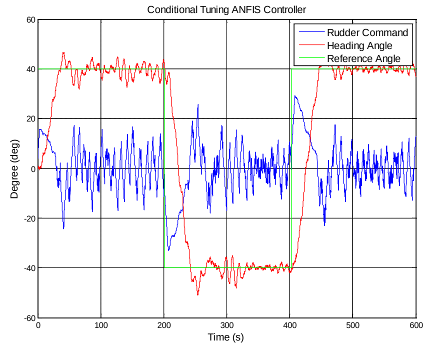

FIG. 27 RESPONSE OF CONDITIONAL TUNING ANFIS CONTROLLER DURING ±40˚ ZIG-ZAG TRACK-KEEPING TASK

Finally, the performance of the conditional tuning ANFIS controller was evaluated by simulating the track-keeping mission shown in Fig. 28 in the presence of external disturbances. The corresponding heading angle and rudder response are shown in Fig. 29.

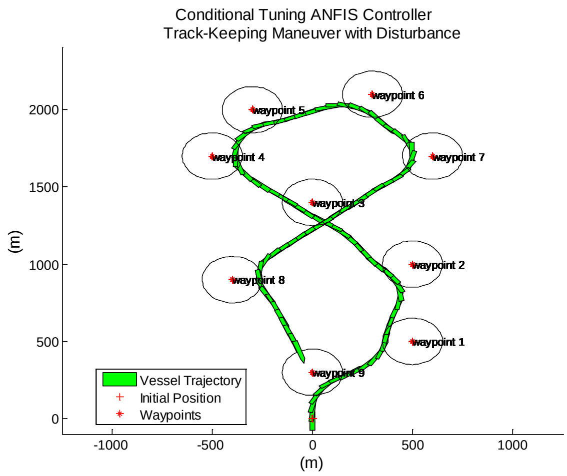

FIG. 28 TRACK-KEEPING MISSION VESSEL TRAJECTORY

Figure 30 shows the overlap track-keeping mission vessel trajectories with three different kinds of controller. Figure 31 illustrates the path deviation distribution for the 3 way-points track-keeping mission. It is observed that the deviation made by the

conditional tuning ANFIS outperforms the others.

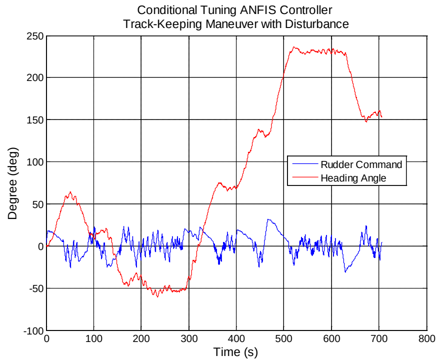

FIG.29 RESPONSE OF CONDITIONAL TUNING ANFIS CONTROLLER DURING TRACK-KEEPING TASK IN PRESENCE OF EXTERNAL DISTURBANCES

The simulation results reveal that the proposed concept has the better robustness than the original ANFIS system, and specifically, confirm that the tracking performance, response speed and overshoot angle are all satisfactory. In other words, the robustness and efficiency of the proposed conditional tuning ANFIS autopilot are confirmed.

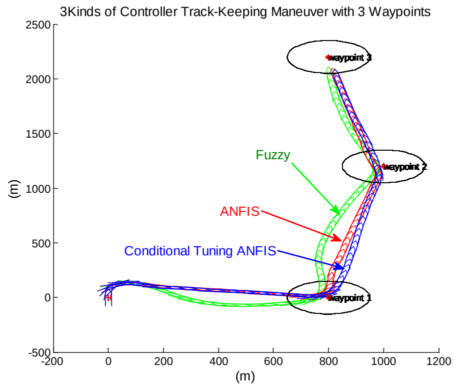

FIG.30 TRACK-KEEPING MISSION VESSEL TRAJECTORIES OF DIFFERENT KINDS OF CONTROLLER

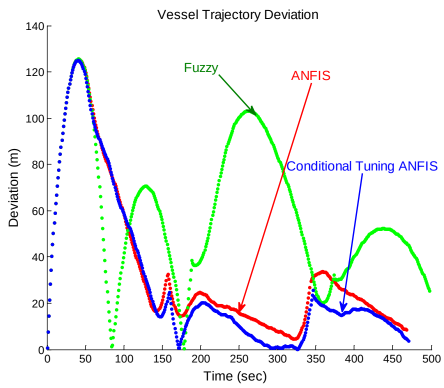

FIG.31 THE PATH DEVIATION DISTRIBUTION

Conclusions

This study has developed a ship steering autopilot based on an ANFIS (Adaptive Network-based Fuzzy Inference System) control scheme. The autopilot requires two inputs, namely the heading angle error and the yaw angle error, and provides one output, namely the rudder command. In designing the ANFIS autopilot, the membership functions are optimized by an Artificial Neural Network (ANN) using the input and output data obtained from a series of course-changing simulations performed using a traditional PD-type fuzzy autopilot. The performance of the proposed autopilot has been evaluated by performing a series of course-changing and track-keeping simulations. It has been shown that the ANFIS autopilot outperforms the conventional PD fuzzy autopilot in terms of both a lower overshoot and a more rapid response. In addition, it has been shown that the performance of the ANFIS autopilot can be further improved by means of a conditional tuning scheme, in which the gains of the autopilot are adjusted adaptively in accordance with the magnitude of the input error signal. The proposed conditional tuning scheme can increase the response speed of the proposed autopilot and reduce the overshoot simultaneously. In a future study, the practical feasibility and robustness of the proposed conditional tuning ANFIS autopilot will be verified by performing a series of track-keeping maneuvers using a small boat in a real-world harbor setting.

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